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Fishing for Complementarities: Research Grants and Research Productivity

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Abstract

Academics are increasingly encouraged to acquire external grants to finance their research, and often hold grants from multiple funders concurrently to ensure the continuity of their work. However, there are concerns that inefficiencies occur when funding is received from multiple sponsors, especially when this originates from different sectors. This study investigates complementarities between public/non-profit and private sector sources of research funding with regard to academic output in terms of publications, research impact and research orientation. The empirical analysis is based on novel data on external public/non-profit research grants and industry funding for tenured engineering academics employed at fifteen UK universities. The results suggest that while research grants are generally associated with higher research outcomes, industry funding decreases the marginal utility of public/non-profit funding by lowering the increase in publication rate associated with public/non-profit grants. At the same time, for more commercially oriented research, measured as its patentability score, we find some support for complementarities between public and private-sector research funding. These results suggest that provision of public grants is crucial to the production of research that is distributed openly through publications and proceedings. Private sector grants are important as they may enable more applied research trajectories for those capable of combining publicly and industry sponsored research.

Keywords: Research Funding, University-Industry Collaboration, Scientific Productivity

JEL codes: L31; O3

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1 Introduction

Across Europe, where universities were traditionally financed through block grants, governments have introduced or increased the amount of funding distributed through grant funding schemes (Stephan, 2012). Grant-based funding has been seen as a mechanism to reward and thus provide incentives for the most able researchers. Stagnating public research budgets further meant that researchers are increasingly encouraged to seek funding elsewhere, e.g. to source funding from industry and other sponsors. Such external research income allows researchers to secure funding for equipment and research assistance, potentially leading to more autonomy and flexibility. It is thus usually accompanied by an increase in research productivity, regardless of the sponsor (Stephan, 2012), and researchers that receive some external funding outperform those who do not acquire external grants (Kelchtermans and Veugelers, 2011).

These developments not only encourage academics to look for grants elsewhere but also mean that many hold multiple grants concurrently. Wang et al. (2012), for example, analyse named sponsors on academic publications in 10 selected countries. They show for the case of the UK that 43% of academic publications acknowledge external funding and report an average of 2.8 funding agents per paper. They also observe that the UK funding system is particularly diversified, with no one funding agent dominating. Nevertheless, despite being commonplace, few papers have analysed the concurrence of different types of funding and their effect on research impact. Some studies argue that multiple grants may result in more impactful research due to more vigorous peer-review or the additional means to support research (Lewison and Dawson, 1998). However, there are also concerns that inefficiencies occur when funding is received from multiple sponsors, for example when it is used to double-fund research (Garner et al., 2013) or due to additional administrative requirements. In addition, tensions could arise as multiple sponsors' goals may not always be aligned, especially with regard to the open dissemination of research results, which could result in fewer research outputs.

Prior literature has voiced concerns with regard to funding from industry, which has been identified as an important source of research income by both universities and by policy makers. While researchers may be able to benefit in their academic work from closer links with industry via insights into applied processes and problems in industry that may provide the ideas for new ground-breaking research (Rosenberg, 1998), their publication quantity and quality may decrease if industry partners limit research freedom by determining research topics and demanding secrecy (Cohen et al., 1998). The question of the relationship between public and private research funding is therefore particularly critical given the need of researchers to seek research funding and the potentially negative effects of industry involvement on some research outcomes (Banal-Estanol et al., 2015; Hottenrott and Thorwarth, 2011; Rentocchini et al., 2014; Toole and Czarnitzki, 2010).

We use data on the research incomes of 807 individual academics at 15 UK universities over a seven year period to investigate the individual and joint effects of public and private funding on the publication and patenting performance of the sponsored academics.[1] Previous studies have shown a positive effect of external funding on publication output, but that larger shares of research funding coming from industry are associated with a decreased publication rate and increased patent rate (Manjarres-Henriquez et al., 2008; Hottenrott and Thorwarth, 2011; Lawson, 2013a; Banal-Estanol et al., 2015). These studies, however, have not addressed the question of whether these relationships are indicative of complementarities or substitution between different types of funding. Our results add to these insights by showing firstly that external research grants are generally associated with higher research output in terms of the number of publications regardless of source. The paper further shows that research quality measured in terms of basic science publications, citations or average impact factor increases only with public funding but not with industry funding. However, industry funding decreases the marginal utility of public funding by decreasing the publication rate increase associated with public grants for publication and proceeding counts as well as for research quality for most of the industry funding distribution. These results are robust to controlling for unobserved heterogeneity and to accounting for the non-randomness of funding allocation. For more applied research outcomes, as measured by the patentability score of an academic's research, the influence of both types of research funding is only positive if they occur simultaneously, providing some evidence for complementarity of public and private-sector research funding. Using industry co-authored publications and patents instead as measures for applied research outcomes, however, shows a positive, but independent effect of both types of funding for most of the industry funding distribution, thus implying additivity. These findings suggest that there are few complementarities in terms of quantity and quality of research outcomes to be realised from concurrent funding and that time constraints and administrative burdens may outweigh possible performance increases. The result that the patentability of research only increases when both types of funding are present, suggests that funding from diverse sources is conductive to more applied research agendas.

[1] The UK has a dual funding structure where public funding for research is provided through two routes: institutional 'core' grants and competitive research council grants. While during the first half of the 2000s research council grants accounted for just 12% of public funding, this was 22% in 2013 (Source: Higher Education Statistical Agency (HESA), own calculation). The amount of 'core' funding and research council provision has moreover decreased in real terms since 2009. These developments have also increased the importance of research grants and contracts from other sources over the past 20 years. During our sample period (2001-2007) industry funding accounted for 10% of total research (non-'core') grants and contracts and for 17%-21% of research grant income in engineering sciences. The HESA data also shows that industry funding is pro-cyclical. It declined after the crisis year 2008 but is increasing again since 2012.

2 Research funding and research productivity

2.1 Industry grants and research outcomes

Industry grants have been identified as a major source of funding for academic research in recent years. In the US the so called competitiveness crisis prompted a series of structural changes in the intellectual property regime accompanied by several incentive programmes designed specifically to promote collaboration between universities and industry (Lee, 2000). Similar incentive schemes were implemented in Europe and elsewhere (Geuna and Nesta, 2006). In many subject areas, including engineering and material science, much of the research would not be possible without the input of industry partners. In a survey of 671 academic scientists and engineers, Lee (2000) reports securing of funds for equipment and research assistants as the principal reason for collaboration with industry. Further, Slaughter and Rhoades (2004) argue that university researchers may be motivated to interact with private companies for reasons other than access to additional research funding, for example finding potential co-authors and ideas for their research agenda. Mansfield (1995) reported that a substantial number of university research projects were initiated through consulting activities with firms and also Lee (2000) identified the acquisition of research ideas as one of the main motives for researchers to pursue joint research with industry.

However, more than just providing an attractive source of additional research funding to supplement the department's core resources, external sponsorship involves contractual agreements and research guidance that could potentially affect academic research. Specifically, the objectives of different sponsors may influence the choice of research topics and the choice of dissemination channels (Slaughter and Leslie, 1997; Cohen et al., 1998; Benner and Sandström, 2000), and industry sponsors may have a particular interest in influencing research and dissemination channels to recover their investments. Accordingly, it has been claimed that industry partners could direct academics towards more applied research and limit or delay the public dissemination of research results (Blumenthal et al., 1996; Cohen et al., 1998). Blumenthal et al. (2006) and Czarnitzki et al. (2015a) find evidence for such publication delay and secrecy associated with industry funding. They conclude that academics' research activities may be compromised by an increase in industry-sponsorship and commercialisation of research.

Empirical evidence on the topic is mixed and partially dependent on the type of activity undertaken with industry. Manjarres-Henriquez et al. (2009) and Banal-Estanol et al. (2015) show a curvilinear effect of the share of industry research funding on publication output which may be indicative of a complementary effect of public and private funding up to a certain threshold. Other studies find a positive link between the share of research income from industry and the extent of patenting (Hottenrott and Thorwarth, 2011; Lawson, 2013a). Lawson (2013a), in the case of the UK, finds a positive effect of industry sponsorship regardless of whether patents are owned by universities or private firms which may indicate that industry links encourage commercially oriented research in academics in general. Other recent studies instead report negative correlations when looking at the effect of income from consulting activities or start-up foundation on publications (Manjarres-Henriquez et al., 2008, Rentocchini et al., 2014 and Toole and Czarnitzki, 2010). Hottenrott and Lawson (2014), finally, analysing a sample of German professors in science and engineering find that those who report industry as a source for research ideas publish and patent less than their peers who source research ideas from elsewhere. Their findings suggest that ideas coming from industry do not translate into more or better quality publications and patents.

These mixed results indicate a need for more systematic analysis of potential complementarities between different types of funding. On the one hand, concurrent funding may open up opportunities for research, recombination of ideas stemming from different projects and consequently the research outputs associated with the research, resulting in complementarities between different funding sources. On the other hand, the combined receipt of public and private research funding could lead to tensions which affect the overall returns to research funding negatively. These tensions and complementarities between different types of funding may, however, likely differ depending on the type of research output that is pursued.

2.2 Basic versus applied science

It seems reasonable to assume that different types of grants are not frictionless adjustable as they are subject to different application and administration costs and are accompanied by different sponsor expectations. If academics receive industry grants in addition to their public grants, their publication output could be reduced due to several reasons. Contractual arrangements with the sponsor may require delaying or withholding results from publication in scientific journals (Blumenthal et al., 1996; Cohen et al., 1998; Czarnitzki et al. 2015a). Earlier research has also found that funding from industry is less targeted at the production of scientific publications and basic research than unrestricted funding from public sponsors (Blumenthal et al., 1996). Funding from industry could thus adversely affect an academic's publication behaviour especially with regard to publications in scientific journals and for more basic research projects (Cohen et al., 1998). Moreover, academics may encounter conflicting incentives and guidelines in their research when receiving funding from more than one agent. Public funding aimed at free dissemination may be contradicted with industry funding which favours the appropriation of knowledge. The direct involvement of industry sponsors in the research process as well as the supervision of contract research and the exchange of results may limit the disclosure of research results or lead to publications that are of lower quality. Moreover, industry-sponsored projects can be related to, but still substantially different from, an academic's other research projects in terms of materials used, methodologies applied or procedures necessary to obtain usable results. Thus, when more time is allocated to industry-sponsored research and development, traditional research could be compromised. In particular, more basic research lines will not be pursued (Slaughter and Leslie, 1997; Benner and Sandström, 2000).

The nature of the sponsor (public vs. private) may therefore proxy for research content that is chosen by the academic vs. research content that is at least partially led by the funder. Although some industry funders may provide funding for blue sky research and some public sponsors may instead ask for tender, previous literature suggests that research that is no longer exclusively led by academics is more likely to happen when the sponsor is from industry (Perkmann and Walsh, 2009). Joint funding could then result in a substitution between different grants and a negative effect of industry funding on the marginal benefits associated with public grants in terms of publications. These effects are likely to be particularly strong for the quality and academic impact of research.

On the other hand, industry sponsorship is also likely to increase the marginal benefits associated with public grants, through the provision of additional funding and contact with real-world problems. If researchers obtain new ideas through links with industry then the expected benefits from public funding placed with these researchers should also increase because of positive complementarities (Mansfield, 1995; Zucker and Darby, 1996; Zucker et al., 1998). This may be particularly visible in shifts towards research that is more applied and commercially-oriented due to a pull or learning effects from industry. Previous empirical work has also shown that, especially in the field of engineering, publications and patents are complementary (Agrawal and Henderson, 2002) and funding could thus benefit both. Academics receiving industry support in addition to public funding may be more likely to recognise and realise the commercial potential of their research. Nevertheless, more applied research may be more likely to be affected by secrecy concerns on the side of the industry sponsor. Banal-Estanol et al. (2015), for example, find publication trade-offs associated with industry collaboration only in the case of applied research publications, but not for more basic research lines. Still, academics receiving industry support in addition to public funding will be more likely to recognise and realise the commercial potential of their research and we expect complementarities in industry and public grants with regard to the patentability of research.

3 Empirical model

We base our empirical model of the effects of research funding on research outcomes on the notion that an academic exerts research efforts aimed at producing measurable outputs. External resources are crucial for scientific production (Stephan, 1996, 2012) and the number and quality of outcomes is expected to be at least non-decreasing with funding received from external sponsors (Kelchtermans and Veugelers, 2011). We consider funding from at least two types of funding agents as inputs to the research output function.[2]

[2] We distinguish public/non-profit from private sector funding. Public/non-profit funding may stem from UK research councils (mainly EPSRC), UK charities, UK government, the EU and other public overseas sponsors. See section 4.2 for details on the funding information.

The research output function in its most general form is then given by:

$$P_{it}(\varphi) = f\left(F_{1_{it-1}}, F_{2_{it-1}}, X_{it} | \varphi\right), \tag{1}$$

Where P_{it} are research outputs and their measures for their quality or research orientation (basic or commercially oriented research), $F_{1_{it-1}}$ and $F_{2_{it-1}}$ denote two different types of funding allocated in *t*-1, where one could be considered public/non-profit, peer-reviewed funding, and the other funding from industry. We use funding split across the award period and lagged by one year to capture the impact of financial resource on scientific productivity in *t*.[3] X_{it} are other explanatory factors such as age, rank or gender. We then include the notion of a positive increase from either type of funding with potential substitution or complementarity effects:

$$P_{it}(\varphi) = \varphi\left[F_{1_{it-1}} + F_{2_{it-1}} + F_{1_{it-1}} F_{2_{it-1}} + X_{it}\right] + \varepsilon_{it} \tag{2}$$

where φ is the vector of parameters to be estimated and ε is the error term given as $\varepsilon_{it}=u_{it}+ v_i+\tau_t$, where v_i is the unobserved individual effect, and τ_t is the time fixed effect. To estimate the existence and extent of any complementary or substitution effect between different types of funding we interact the two funding variables and estimate their joint effect. In addition, while research outputs are assumed to benefit from research grant input, this does not rule out diminishing returns as shown in Manjarres-Henriquez et al. (2009) and Banal-Estanol et al. (2015) and these should therefore be considered when estimating funding effects. .

The analysis takes two different approaches, a dynamic feedback model estimated via Poisson and GLS regressions and dose-response functions based on the Generalized Propensity Score (GPS) approach. The GPS for continuous treatments is an extension of the more commonly applied propensity score methods for binary treatments (Rosenbaum and Rubin, 1983, 1984) and multi-valued treatments (Imbens, 2000; Lechner, 2001) which takes into account the selectivity in the grants awarding processes (Bia and Mattei, 2008; Guardabascio and Ventura. 2013). Both approaches are discussed in Section 5.

4 Data and descriptive analysis

4.1 Data

The following analysis tests for direct and joint effects of different types of research funding on several measures for research output. The analysis is based on a novel data set of tenured engineering

[3] The exact lag between funding and publication will depend on the individual project. A look at a random sample of research council grants awarded in 2006 in engineering (Source: "Gateway to Research", the UK online research council funding database) showed that about half reported their first publication in 2007 already. A one year time lag is therefore adopted here.

academics employed at 15 UK universities containing information on external public research grants and industry funding, journal publications, citations to these publications, conference proceedings and patents.

The original database was built using yearly staff registers in academic calendars and on academic websites of 40 UK universities for the 1986 to 2007 period.[4] All academics working as lecturers, senior lecturers, readers or professors at engineering departments were identified, their career progression recorded and their names manually matched to their publication and patent records (see Banal-Estanol et al. 2015 for a detailed description of the database).

To gain access to funding information for academics, we contacted all the engineering departments by email. Fifteen departments[5] provided us with detailed records containing information on private and public research grants received by their departmental staff during the period 2001 to 2007[6] (see Table A1 in the Appendix for a list of universities). Information on consultancy contracts was not solicited. We manually matched this information to the 885 academics that worked at one of the 15 universities for a minimum of six years during the 2001-2007 period.

To acquire full publication and patent records for the period 1998 to 2007 (the sample period plus a three year pre-sample time-window), we further complemented the original database with publications and patents for the years that were not covered by the original database. This includes years spent outside the sampled engineering departments, PhD or postdoctoral periods, or, in the case of patents, filings made after 2005 as these were not included in the original sample. We further collected data on published conference proceedings. Journal and conference publications were obtained from the ISI Web of Science (WoS) database. Patent application data was obtained from esp@cenet (the European Patent Office (EPO) web-interface), which allows searches for patent applications filed with the EPO,

[4] The sampling involved firstly the identification of the 89 universities offering engineering courses based on the 2001 Research Assessment Exercise (RAE). All 39 pre-1992 institutions were explicitly excluded at the time of data collection. For 10 additional institutions no staff data could be collected. The 40 sampled universities receive the bulk of research funding in engineering (>80% from all sources [Source: 2008 RAE]), and thus represent the most research active engineering departments.

[5] The 15 universities do not differ significantly from the original sample of 40 in terms of the number of publications and patents by individual academic staff, but staff receive a slightly higher amount of research council funding (KS-test: p=0.040).

[6] The period 2001 to 2007 is the preferred period for this analysis as it covers a larger number of universities and represents the assessment period for the 2008 RAE. The research information can therefore be expected to be fairly standardised across the 15 institutions and adjusted to the requirements of the RAE. It is therefore considered most reliable and comparable across institutions.

the UK Intellectual Property Office (UKIPO), the US patent office (USPTO) and other national patent offices. We downloaded all WoS and espacenet entries with the same last name and first initial before proceeding to clean all database entries manually to assure correct matching to individual academics. In the case of patents we considered all patent applications that named the focal academic as an inventor regardless of whether they were filed by the universities or third parties, e.g. industry or government agencies.[7] Further, as each invention can lead to multiple patent applications (e.g. at different patent offices), we additionally verified each entry with the International Patent Documentation Center (INPADOC) that contains information grouped around a patent family, enabling us to uniquely identify the original invention and avoid multiple counts. In the remainder of the paper the term patent will refer to patent families grouped around an original priority patent (as defined in INPADOC) and not to individual patents or patent applications. The term will also be used regardless of whether the patent was granted or not. We recorded the filing date of the original priority patent as this represents the closest date to invention and collected all patents filed between 1998 and 2007.

We supplemented this data with PhD year and subject information. PhD information was taken from *Index to Theses*, an online database which lists theses accepted for higher degrees by the universities of the UK and Ireland. It provides information on PhD institution, year and subject area. For academics not listed in the database we searched their websites and gathered PhD details from the library catalogues of the PhD awarding university.[8] We further collected department information regarding staff and student numbers from HESA. Data was available from 2003 onwards and 2003 values were applied to earlier years.

After exclusion of incomplete records, the final data set contains 807 engineering academics. Of these individuals, 58% received some external funding at least once during the six-year observation period.

4.2 Variables and descriptive statistics

The descriptive statistics for the sample are reported in Table 1. The main variables can be categorised as research output indicators, research funding as well as individual, departmental and institutional controls. Correlations between the funding and output indicators are reported in Table A2.

Research Outputs

[7] Lawson (2013b) showed that in UK engineering more than 50% of academic inventions are not owned by the university but by private firms, government or individuals.

[8] This concerned some PhDs awarded in the UK that were not submitted to *Index to Theses* as well as PhDs awarded outside the UK and Ireland.

Our main outcome measure is the annual count of publications ($PUBLICATIONS_{it}$) for each academic i. The mean number of publications during the observation period is 2.26 per academic per year. Further, 8% of the academics in our sample did not publish during the entire six year period and 30% published less than one journal article per year.

To measure the quality or 'basicness' of research we use two approaches. First, we measure the average number of citations received in the first five years after publication ($AV.CITATIONS_{it}$), which represents an established measure for research quality. By applying a fixed citation time window we further ensure that all publications had the same time to accumulate citations. The average number of citations in the sample is 2.88. As a second approach we use the number of publications in basic science journals as a measure for more fundamental, science driven research. The measure is based the journal classification by Narin et al. (1976) that classified basic and applied type journals based on cross-citation matrices between journals.[9] The authors distinguish between four categories where 1 is the most applied and 4 the most basic. We consider a publication to be science-oriented or basic if it falls in categories 3 or 4 ($BASIC_{it}$). The mean number of publications in such journals is 0.64.

To measure the commercial applicability of each academic's research, we follow Azoulay et al. (2009) and construct a patentability variable ($PATENTABILITY_{it}$) that uses title words in publications to identify the focal academic's research field and applies weights based on the extent to which these title words have appeared on publications that can be linked to patents. Specifically, we use patent-publication-pairs (Murry, 2002) of UK engineering academics as a benchmark for patentable research and then compare the title words used by each academic to this benchmark. The procedure is described in detail in Annex B.

In addition we construct a series of outcome variables that can serve as robustness checks in the analysis of funding complementarities. We use the number of proceedings as an alternative outcome count measure to publications ($PROCEEDINGS_{it}$). Conference papers represent a more immediate outcome of research, providing access to recent discoveries (Lisee et al., 2008) and are considered as very important in several areas of engineering. As an alternative quality measure we make use of the journal impact factor (JIF), a measure of impact that is based on the average number of citations received by a journal's articles in a specific year, in the first three years. Though not a direct measure of quality, the JIF represents the importance attributed to a particular journal. We calculate the average impact of academic i's publications ($AV.IMPACT_{it}$) by weighting each article by the corresponding journal's JIF in t and dividing by the number of publications. As robustness check for commercially oriented research we use two measures. The first is the share of publications with at least one author-

[9] Here we use the 2005 classification updated by Kimberley Hamilton for the National Science Foundation (NSF).

address in industry ($INDPUB_{it}$) as suggested by Azoulay et al. (2009). The second is the most direct measure of commercialisation, namely, whether the academic filed a patent in t ($PATENT_{it}$). Results using these measures are presented and discussed in Appendix C.

[Tables 1 and 2 about here]

Research Funding

The research income information includes the name of the principal investigator as well as data on funding source, award date, grant period and funding amount. We can attribute grant-based income to: (1) industry and business, (2) public/non-profit funding agents, including UK research councils (mainly EPSRC), UK charities, UK government, the EU and other public overseas sponsors.[10] These represent all funding agents available to UK academics. The amount of funding is significantly higher for public grants with an average of more than £150,000 per grant and only £60,000 for industry grants. All funding amounts were split across the award period to avoid focussing the entire amount at the start of the grant and to account for the length of the research project. In other words, if the grant lasted two years we split it equally across those two years, if it lasted over three or more years, the first and the last years (which are assumed to not represent full calendar years) received half the share of an intermediate year. This was done in order to account for the on-going benefits and implications of a project.

After excluding some outliers[11] academics receive on average £32,000 per year in external funding. Industry funding amounts to approximately £6,000 per academic per year, while public funding provides approximately £26,000, with the majority being sourced from UK research councils and charities (circa £20,000). If we only consider academics that receive some funding during the observation period, the average amount of external funding per year is £55,400 with approximately

[10] Funding from charities is included in public/non-profit funding as selection mechanisms mirror those employed by research councils. Selection is based on peer-review and sponsorship is provided for blue-sky research, making these very prolific grants. Sponsors include Wellcome Trust or Leverhulme Trust. UK government sponsorship may be considered contract research, however, a robustness check omitting government funding from the public funding measure showed that results remain robust (results available from the authors upon request).

[11] Outliers were identified using average values of leverage and (normalised) residuals following a linear regression of funding on publication outputs and are excluded using DFFITS (Belsley et al., 1980) which measures the change in the predicted value when the i^{th} observation is deleted. We follow Bollen and Jackman (1990) and exclude observations with DFFITS>1, meaning that the observation shifts the estimate by one standard deviation. We repeat the process for all funding variables and in total exclude 14 observations, most of which are EU funding outliers.

£9,800 coming from industry and £45,600 from public sponsors. The majority of academics receive funding from more than one type of funding agent during the observation period; 43% of academics, however, receive no external funding at all. Of those that receive external funding at least once, 60% are sponsored by industry (35% of the total sample). In terms of funding volume, UK research council and charity funding accounts for 65% of all external research income, funding from industry accounts for 17%, followed by EU with 11% and UK government with 8%.

Looking at funding received during one period, we find that 42% of funded academics receive public and industry funding simultaneously at least once. Appendix Table A2 reports the correlation between different types of funding and the outcome measures. We find a strong positive correlation between public and industry funding. All publication count and quality measures correlate stronger with public funding, but the patentability measure has very weak correlations with both types of funding and industry co-authorship and patents are stronger correlated with industry funding than public funding..

Control variables

We control for a series of individual and institutional attributes of the academics that may affect research outcomes. Previous literature has documented life-cycle effects (Levin and Stephan, 1991). We control for these effects by including the academic age, (*PHD_AGE*) of the academic, calculated as the difference between the current year and the year of the PhD. We further include a dummy for those academics that do not hold a PhD (*NO_PHD*), which represents 7% of the sample. We also account for seniority by including a dummy for being a professor. We also control for gender (*FEMALE*) as previous literature has found a gender bias in both funding and academic productivity (Stephan, 2012). However, women account only for 7% of academics in our sample. Funding and research outcomes likely differ by scientific field. We control for subject specialisation based on the subject of the PhD. In our sample 22% of academics graduated in electrical and electronic engineering (*ELECTRICAL*), 21% in civil engineering (*CIVIL*), 15% hold a PhD in chemical engineering (*CHEMICAL*), 15% in physics (*PHYSICS*) and 13% in mechanical engineering (*MECHANICAL*). Just 8% have a background in life sciences (*BIO*).

Several other factors are of importance when estimating the relationship between funding and productivity, foremost an academic's teaching and administration load. We cannot measure these at the individual level but information is available at the department level from HESA. These measures include the Student-Staff-Ratio *(SSR)*, the total staff-to-support-staff-ratio *(TSR)* and the ratio of research only staff over academic staff *(RSR)*. In addition, the university's overall share of income from research grants is used to proxy institutional differences in the access to funding.

4.3 Analysis of funding profiles

To get a better picture of the different funding profiles of academics in the data, Table 2 reports descriptive statistics for individual level variables by type of funded academic. Academics are allowed to move between groups depending on their funding status in t-1. We differ between observations where an academic receives (1) no public or industry funding, (2) only industry funding, (3) only public funding and (4) both, industry and public funding. The basic descriptive results show that all four groups are significantly different on most of the variables. They also show that academics who received funding produce more publications than those who do not. However, this difference is significant only for academics with some public funding. Further, academics receiving both industry and public grants are most productive in terms of publications, citations and basic publications. This group of highly sponsored and diversified academics is also the group with the highest number of conference proceedings, the highest average impact factor and the highest propensity to patent. This is in line with the literature on star scientists (Zucker and Darby, 1996; Zucker et al., 2002) that suggests strong complementarities between high scientific ability, commercialisation and funding success. The patentability of research, however, does not differ by funding profile while the share of industry co-authored publications is higher for those with industry funding.

In terms of funding amounts, it becomes clear that academics that source funding from more than one source raise significantly more funding than academics that rely on just one source. This suggests that some academics may be more successful than others in applying for grants because of their research agendas or individual talent. It could further reflect that, because public grants are primarily distributed based on peer review and can be expected to benefit the most able academics, industry may look at public grants to inform their own funding decision and to identify potential partners for research (Perkmann et al., 2013).

[Table 2 about here]

5 Method and Results

5.1 Regression analysis for research outcomes

As a first estimation strategy we use count data models to estimate research outcomes, as the number of research outcomes (publications and citations) are by nature positive and the data is characterised by a large number of zeros. We assume the outcome variables to have a Poisson distribution. A key assumption of the Poisson model is the equality of the conditional mean and the conditional variance, which is typically violated in applications leading to overdispersion, as is the case with publication and citation counts. However, although the negative binomial model may offer a solution that allows for overdispersion, it is only consistent and efficient if the functional form and distributional assumption of the variance term are correctly specified. The Poisson model, on the other hand, is consistent under the assumption that the mean is correctly specified even if overdispersion is present when robust standard errors are imposed (see Wooldridge, 2002, p 646-653). It is also robust in the presence of large numbers of zeros, dependence over time as well as cross-sectional dependence (Bertanha and Moser, 2014).

As we can expect decreasing marginal returns to funding even if it comes from the same funding source, we also include the quadratic term thus employing a specification of the form:

$$E(P_{it}) =$$
$$exp\{\beta_0 + \beta_1[F_{1_{it-1}}] + \beta_2[F_{1_{it-1}}]^2 + \beta_3[F_{2_{it-1}}] + \beta_4[F_{2_{it-1}}]^2 +$$
$$\beta_5[F_{1_{it-1}}F_{2_{it-1}}] + \beta_6[F_{1_{it-1}}F_{2_{it-1}}]^2 + \beta_7\left[\left(F_{1_{it-1}}\right)^2 F_{2_{it-1}}\right] +$$
$$\beta_8[F_{1_{it-1}}(F_{2_{it-1}})^2] + \gamma X'_{it} + \varepsilon_{it}\} \qquad (3)$$

In the case of continuous variables in non-linear models the interaction effect is the cross-derivative of the expected marginal change in publications or citations. For example, the marginal effect of funding $F_{1_{it-1}}$ on our dependent variable P_{it} is derived as the first derivative of (3):

$$\frac{\partial E(P)}{\partial F_1} = (\beta_1 + 2\beta_2 F_1 + \beta_5 F_2 + 2\beta_6 F_1 F_2^2 + 2\beta_7 F_1 F_2 + \beta_8 F_2^2)E(P) \qquad (4)$$[12]

Then, derived from (4) the marginal change of funding $F_{1_{it-1}}$ on the dependent variable P_{it} with respect to the interaction term $F_{2_{it-1}}$ can be written as:

$$\frac{\partial E(P)}{\partial F_1 \partial F_2} = (\beta_5 + \beta_6 F_1 F_2 + \beta_7 F_1 + \beta_8 F_2)E(P) + (\beta_1 + 2\beta_2 F_1 + \beta_5 F_2 + 2\beta_6 F_1 F_2^2 + 2\beta_7 F_1 F_2 +$$
$$\beta_8 F_2^2)(\beta_3 + 2\beta_4 F_2 + \beta_5 F_1 + 2\beta_6 F_2 F_1^2 + \beta_7 F_1^2 + 2\beta_8 F_2 F_1)E(P) \qquad (5)$$

Any two types of funding are classified as complements if the sign of the cross derivative is positive, i.e. if an increase in industry funding increases the marginal utility of public funding. If instead, an increase in industry funding decreases the productivity gains of public funding they are considered as substitutes on the outcome variable P_{it}. If the cross-derivative is zero then we would observe a purely additive relationship between the two types of funding where one could replace the other without compromising its marginal utility.

In addition to publication based productivity measures, we also estimate the effect of different types of funding on the patentability of the research content. We estimate OLS regression models with clustered, robust standard errors and log the dependent variable to estimate the elasticity of patentability to increases in research funding. All funding measures are logged after adding 1 to correct for their skewed nature in both Poisson and OLS models.

Theory suggests that research activity is subject to dynamic feedback (Dasgupta and David, 1994) as each academic's performance is driven by cumulative unobserved factors (u_{it}), e.g. learning, which are not controlled for through fixed effects. Blundell et al. (1995) therefore argue that it is important to

[12] Subscripts omitted.

consider continuous, sample-period dynamics when modelling research outcomes. To proxy for u_{it} we thus include the stock of the dependent variable into all models.

We therefore estimate pooled models, which have the advantage that they allow the inclusion of dynamic effects. However, they do not control for unobserved individual heterogeneity (v_i). In our case such unobserved effects could be specific skills of each academic that are positively correlated with the right hand side variables such as external funding and a potential endogeneity problem arises. For example, the literature suggests that more able academics have many more opportunities to receive funding as grant awarding bodies screen academics for their ability and sponsor the most productive. If unobserved individual heterogeneity were present, the estimated coefficient of the funding variables would be upwards biased. We can cope with this challenge if pre-sample information of the dependent variable is available. Specifically, Blundell et al. (1995, 2002) suggest a solution which controls for individual heterogeneity by specifying the average productivity of the academic before she enters the sample. The pre-sample mean of the dependent variable is a consistent estimator of the unobserved individual effect (v_i) if it mainly corresponds to the intrinsic ability of an academic and her motivation, both factors that are not directly observable but may affect scientific productivity. Following Blundell et al. (1995, 2002) we can therefore account for unobserved individual heterogeneity by using pre-sample information of publications and citations. We include the log of the average number of publications (or their citations) published in a pre-sample period (in the period 1998 to 2000). In cases where the pre-sample value is zero, we include a dummy to capture the "quasi-missing" value.

The stock of the dependent variable for the years following 2000 and the pre-sample value of the dependent variable for the period 1998 to 2000 are thus included in all Poisson estimations. This dual approach helps to address the problem of endogeneity that arises from correlated individual effects and through dynamic feedback from the dependent variable.[13] Year and university dummies are included in all regressions to control for potential time or institution fixed effects. In the OLS estimation for patentability we are not able to effectively control for pre-sample heterogeneity due to a lack of available data for the pre-sample period. The lagged dependent variable thus alone accounts for dynamic feedback. The dose response analysis reported in section 5.2 serves as a more robust analysis by accounting for selection into funding levels more directly.

Tables 3 and 4 report the coefficients of our models. We firstly report the results for the control variables, which are consistent across the two funding specifications (i.e. models that include overall funding receipt and those that consider public and industry funding). Professors publish significantly

[13] Regressions do not suffer from multicollinearity when stock and pre-sample measures are included. The collinearity diagnostics show a vif (variance inflation factor) < 2 for all stock and pre-sample measures.

more and of higher quality than junior academics, perhaps due to their experience and better access to resources. They do not publish more articles in basic science journals, however, and they publish research that is less commercially oriented. We do not find a significant difference between the research outcomes of men and women. Academics that do not hold a PhD also produce significantly fewer publications, receive fewer citations and are less likely to publish research that is of commercial value than others. Productivity and publication quality declines with age, while research content is not affected. Publication and average citation numbers are lower in more applied fields of engineering such as civil and mechanical engineering. The patentability of research does not differ by subject area. However, academics with a background in either physics or life sciences report the highest numbers of basic science publications. University fixed effects and year effects are jointly significant. Moreover, our measure for teaching load has a significantly negative impact on publication numbers. Our measure for managerialism in terms of the share of administrative staff at the department level is associated with lower publication numbers, while higher numbers of research support staff are positively associated with patentability. The pre-sample mean and the dynamic feedback variables are both positive and significant in the research output estimations pointing at the importance of controlling for individual unobserved effects.

[Tables 3 and 4 about here]

For the interpretation of the funding effects we need to consider marginal effects for the main effects and their second order terms and cross-derivatives for the interaction effects (following eq. (4) and (5)). Following Greene (2010), we present these effects graphically. Figures 1a-1d report the effect of overall funding for different funding values in the top left corner, the effect of public funding in the bottom left corner and the effect of industry funding in the top-right. We plot the joint effect of public and industry income as the impact of industry funding on the average marginal effect of mean public funding (bottom right corner of Figures 1a-1d). This representation allows us to see whether an increase in industry funding increases or decreases the effect of public funding and thus provides evidence for complementarity or substitution.

[Figures 1a-1d about here]

The results show that external funding has an overall positive effect with decreasing returns on research outcomes (albeit insignificant for citations), supporting our positive research output function assumption. For illustration, doubling the funding from the sample mean increases the publication numbers by 0.18 publications which corresponds to 18% of the sample median of 1 publication per year. Differentiating between public and industry funding we find that while the number of publications increases (with decreasing returns) with the amount of public and the amount of industry funding (Figure 1a), research quality, measured in terms of basic science publications and citations (Figures 1b and 1c), increases only with public funding but not with industry funding. Patentability increases with public and industry funding, thought the increase associated with industry is very small (Figure 1d).

The cross-derivative of the interaction term is negative and significant for publication counts, revealing a negative effect of industry funding on the effect of public funding (Figure 1a, bottom right). This indicates that while public funding correlates positively with publication numbers, the joint effect of industry and public funding is negative, offsetting part of the positive productivity effect of public grants. For basic publications we find a weak negative effect that albeit significant makes little changes to the overall number of publications published from public grants (Figure 1c). This could be due to the low number reported here and to the generally rather applied nature of engineering. For citations (Figure 1b), we find the squared interaction term to be positive and significant for higher amounts of industry funding. This points to a quality-enhancing effect at higher values of joint funding, though again the effects are very small. For patentability, instead, we find a positive interaction effect (Figure 1d). Thus, while we only observe a small individual effect of industry funding, complementarities for commercially oriented research are realised when both public and industry funding are received simultaneously.

5.2 Dose response analysis

The parametric estimations reported above may suffer from identification problems that arise from the fact that research funding is not randomly distributed amongst academics. Successful grant recipients are likely to differ from non-recipients in important characteristics. Ignoring these differences in the likelihood of receiving grants in the first place, may bias the estimates of the effect research grant income has on research outcome variables. Econometric evaluation techniques address such potential selection bias (see Heckman et al., 1999; Frölich, 2004; Imbens and Wooldridge, 2009, for surveys). The aim of the following analysis is to estimate the treatment effects of research grants on scientific outcomes taking these concerns into account. Given the characteristics of the academics in our sample and the cumulative nature of research grants, we choose a method that can deal with repeated and multiple grant receipts as well as with the continuous nature of the treatment variables. In particular, we employ a Generalized Propensity Score (GPS) method for continuous treatments which is an extension of the popular propensity score methodology for binary treatments (Rosenbaum and Rubin, 1983, 1984) and multi-valued treatments (Imbens, 2000; Lechner, 2001). Based on the GPS we can estimate a dose-response for research outcome as a function of the amount of funding received. The GPS has a balancing property similar to the binary propensity score ensuring that, conditional on observable characteristics, the level of the treatment can be considered as random for units belonging to the same GPS strata (Hirano and Imbens, 2004). This approach has the advantage over other parametric models that it avoids assumptions about functional forms and error term distributions. Based on the probability of receiving a certain treatment level conditional on a set of observable characteristics X, the GPS is an index function summarizing a wider set of observable characteristics affecting the probability of receiving the treatment level and thus has the advantage to avoid the "curse of dimensionality" associated with exact matching techniques (see Rosenbaum and Rubin, 1983).[14]

We follow the method proposed by Guardabascio and Ventura (2013) who build on earlier work by Bia and Mattei (2008) for estimating the dose-response function for cases in which the treatment variables are non-continuous and not normally distributed like in our case of funding amounts. In essence, this method estimates the dose-response function (DRF) through a generalized linear model which is more flexible in terms of underlying data structure. The estimation of the DRF thus follows from a two-step procedure in which we first estimate the parameters θ and ϕ of the conditional distribution of the treatment given the covariates that explain the selection into the treatment:

$$\widehat{GPS_i} = r(T,X) = c(T,\hat{\phi})exp\left\{\frac{T\hat{\theta}-a(\hat{\theta})}{\hat{\phi}}\right\} \tag{6}$$

where T_i indicates the treatment level and X a set of individual, departmental and institutional characteristics, which are likely to predict research grant success.

In the second step, the conditional expectation for the outcome variable, given T_i and GPS_i is modelled such that:

$$\begin{aligned} \varphi[E(Y_i|T_i, GPS_i)] &= \omega(T_i, GPS_i; \alpha)] \\ &= \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 GPS_i + \alpha_4 GPS_i^2 + \alpha_5 T_i GPS_i. \end{aligned} \tag{7}$$

In order to obtain an estimate of the entire dose-response function, we estimate the average potential outcome for selected intervals of the treatment. To assure enough observations per treatment interval, we divide the sample according to the distribution of the respective funding amounts (see Table A4 in Appendix A). Within each interval cut, we compute the GPS from Eq. (6) at the median of each cut of the treatment. Each cut is then further divided into blocks and within each block we calculate the mean differences of all covariates between individual belonging to the block and those belonging to other cuts. All these mean differences are then combined based on block-size weights.

We model the selection stage close to Rentocchini et al. (2014). Important variables are previous grant receipt (before *t-1*) by type of funding and the individual's prior research performance in terms of publications and patents, which are included to account for cumulative advantage in the application and selection process. The individual's professorial rank, gender and career age are included to

[14] Matching estimators have been applied and discussed in a variety of contexts and by many scholars, amongst which Angrist (1998), Dehejia and Wahba (1999), Heckman et al. (1997, 1998a, 1998b), Lechner (1999, 2000) and Smith and Todd (2005).

account for experience and the research sub-field to account for differences in opportunities and resource demand. We further include a number of departmental factors such as the student-staff-ratio *(SSR)*, the total staff-to-support-staff-ratio *(TSR)*, and the research staff over academic staff ratio *(RSR)*. To control for institutional characteristics we include the university level share of income from research grants in total funding, information that is available from HESA. Year dummies are included to capture time trends. Appendix Table A3 shows the estimation results for the GPS. Most of the explanatory variables are significant and show the expected signs. In particular, past grant receipts, rank and academic age explain future grant receipts. Moreover, prior research performance has the expected positive sign capturing the effects of past research performance on grant success.

Appendix Table A4 shows mean differences between the variables after the matching procedure. For most of the predictors we do not observe any significant differences between the treated individuals and the control group. There are, however, some differences left due to the relatively small number of grant recipients which limits the number of potential controls taken from all other treatment levels. However, the most critical predictors such as past grant receipts and past research performance are balanced for all intervals.

Figure 2a shows the respective dose response function for all funding, public funding and industry funding respectively. All research outcomes are increasing in the level of funding with the exception of patentability. Differentiating between public and industry sources of funding, however, provides a more nuanced view. First, the dose response function confirm the results from the Poisson models that publication numbers and citations are increasing with funding amounts for both public and industry grants, while basic publications only increase with funding from public funding sources. Figure 2b shows the estimated responses for the joint receipt of public and industry funding. More precisely, we estimate the dose response of public funding at different levels of industry funding. We then plot the estimated treatment effect associated with average public funding at different percentiles of the industry funding distribution, given that both types of funding had been received jointly. Confirming the main insights from the parametric estimations, we find that the impact of public funding on publication counts, the average number of citations and basic research publications is lower for higher levels of industry funding. For the patentability score[15], on the other hand, we see a different pattern suggesting positive joint effects although the confidence bands are wide and the estimate is only statistically significant at the 75 percentile.

[Figures 2a and 2b about here]

[15] Note that we drop four observations because they were considered as outliers in the patentability score compared to the other values in the treatment interval in order to exclude their strong impact on the results.

Taking the selection into external funding levels into account still provides results which are comparable to the Poisson estimations. While the estimation is able to balance key characteristics that may affect selection into funding, differences in unobserved characteristics may remain. Results using robustness measures are reported in Appendix C.

7 Conclusions

This paper empirically investigated the existence of complementarities between public/non-profit and private-sector grant-based research funding on scientific performance. The question of complementarity or substitution between different types of funding is gaining in importance due to academics' increased reliance on research grant income and the co-occurrence of funding from different sponsors with goals that may not always be aligned. In the UK, for example, university income from funding councils has declined in real terms over recent years and the share of research income sourced from external funders is continuously increasing as a consequence. Further, in the UK, research councils require the open dissemination of all results and data following project conclusion (RCUK, 2015), which may be in conflict with goals expressed by other funders, in particular industry sponsors.

Results from dynamic feedback models and dose response estimations, that take into account the selection on observable individual level characteristics in the grant awarding process, showed that public and private research grants are positively associated with publication numbers and research quality. The results further showed that only public funding is associated with more basic science publications, while industry grants have no significant effect. In terms of the joint effect of public and private funding, the results suggest that obtaining research funding from both source types simultaneously reduces publication numbers and quality compared to receiving public funding alone. This negative joint effect for publication counts and their quality could be explained by the quicker turn-around required by industry sponsors that does not allow the pursuit of a higher number of research publications or the development of high impact research. In addition, other time-trade-offs associated with holding multiple grants may affect publication quantity and quality regardless of the type of sponsor. The administrative efforts required to manage multiple grants could also leave less time to develop research publications. Finally, double disclosures due to double funding of research may lead to lower impact publications. These results thus indicate that academics may find it difficult to recognise and realise potential complementarities between their publicly funded work and industry-sponsored projects in terms of publication based outcomes.

Conversely, for commercially oriented research, as measured by the patentability of research content, we find that public and industry grants are complements. This complementarity, however, does not carry across to other types of commercial outputs such as patents or industry co-authored publications. These insights suggest that while joint funding leads to more applied research, academics may still lack the skills or mind-set required for successful patenting and/or joint-publications resulting from research that involves various sponsors. Still, patents and joint industry publications do not suffer from substitution effects between projects funded by public and industry sponsors, and results suggest an additive effect of public and industry funding.

The results of this paper help to inform the debate on how industry and public funding jointly affect research productivity. Previous research has shown that academics engaged with industry or in commercialisation are less likely to share their results and materials (Shibayama et al., 2012; Czarnitzki et al. 2015b). Blumenthal et al. (2006) and Czarnitzki et al. (2015a) show evidence of secrecy clauses for academics with industry grants that may also affect the output of publications from public grants. Our study adds to this previous work pointing to disclosure and dissemination conflicts in the case of UK engineering academics.

In terms of policy implications, we can conclude that co-sponsorship affects different research outputs differently. It remains important to provide public grants to fund research that is distributed openly through publications and proceedings. Private sector grants nevertheless remain very valuable to those academics capable of combining publicly financed research with industry projects to enable more applied research trajectories. However, further studies would be required to determine whether these findings hold for other more basic scientific fields.

This study is a first step in exposing the interactions between different types of external funding and different research outcomes. We concentrated on the field of engineering, which is traditionally associated with applied research and industry relations. We therefore strongly encourage further research to consider other disciplines as funding environments continue to shift. The evidence presented here shows that this shift may not be without consequences for the development of the science base, even in applied sciences like engineering. Ours can only be a first attempt and more research is clearly needed to pin down the mechanisms behind the productivity effects of grant-based research funding. In addition, in absence of experimental settings for the context of this study, our research design is based on matching techniques that can only account for selection on observables. Unobserved factors explaining both funding received as well as research outcomes may, however, matter for the presented results. We therefore encourage further research based on other identification strategies to pin down causal effects.

With the comparability of our results in mind, we suggest further research on the dynamics underlying the sponsor-research outcome relationship in both qualitative and quantitative approaches. In particular, the debate on research funding would benefit from an investigation into whether and how funding relationships affect both short-term scientific outcomes and the shaping of scientific careers. It may be that academics specialise in certain types of grants and sponsors, and hence the type of research output they pursue. The issue of double funding also warrants further investigation, i.e. whether similar effects are found for concurrent grants from sponsors that are similar in nature.

While consulting and informal contacts with industry tend to be highly correlated with contract research for industry (Gulbrandsen and Smeby, 2005; Ponomariov and Boardman, 2008), future research may also address the difference between pure consulting activities, which is are less research oriented and requires high levels of contact, and contract research, which is more research oriented. If the former type of activity outweighs the second type, the overall effect on publications would be negative, but may be driven by consulting and not industry grants in general.

Finally, it is important to stress that this study does not evaluate other benefits that may come from co-sponsorship. A more comprehensive assessment is therefore needed to establish any benefits for students or teaching as well as benefits for the sponsoring firms, which would contribute to the social returns from science and may therefore be of greater policy relevance than publications and patents.

APPENDICES

Appendix A: Supplement figures and tables

[Table A1 to A4; Figures A1 to A2b here]

Appendix B: Patentability Measure

Following Azoulay et al. (2009), we construct a measure of patentability using title words on publications to "identify the areas in which [academics] have conducted research and then apply weights to these areas based on an (endogenous-to-the-sample) measure of the extent to which other scientists working in these areas have patented their discoveries" (p: 654).

We use double disclosures, i.e. research that resulted in both patents and publication, as a benchmark for patentable research. Previous research has argued that scientific and technological disclosure co-evolve and stress the importance of such 'dual knowledge' (Ducor, 2000; Murray, 2002; Murray and Stern, 2007). The use of such a benchmark for patentable research is an improvement on Azoulay et al. (2009) who used all publications of patenting academics as benchmark, regardless of whether these publications were linked to patents. We build up the benchmark sample of publications based on all EPO patents (including applications) by engineering academics at 40 UK universities with priority dates between 1997 and 2005 (in total 917 patents; see Banal-Estanol et al. 2015 for a description of the data). The benchmark is thus not entirely endogenous-to-the-sample as we consider patents from a larger pool of engineering academics. This data was shared with the APE-INV programme (http://www.academicpatenting.eu) which matched these patents to Web of Science listed journal articles published between 1999 and 2007 (the shortened time window was due to data access restrictions), that have at least one common author and, following a text analysis of titles and abstract, deal with the same research result (see Lissoni et al. 2013 for a detailed description of the methodology). After matching, only the best-matched patent-publication pairs (PPPs) with similarity index values in the top 25% of the first percentile were retained, corresponding to 730 pairs, or 238 patents and 652 publications.

The 652 PPP publications (which include 116 publications by our focal academics) are considered as benchmark for patentable research, to which we compare the research of each academic in order to generate a patentability score. In building this measure we closely follow Azoulay et al. (2009) in that we produce a list of keywords j used by academic i in t, and count the number of times (n_j) that j appears on publications. We then calculate the proportion of the total number of keywords (n_k) it represents and finally apply a patentability weight w before taking the sum over all keywords:

$$Patentability_{it} = \sum_{j=1}^{J} w_{j,t-1}^{i} \frac{n_{ijt}}{\sum_k n_{ikt}}.$$

The weight *w* is based on the number of times the keyword *j* appeared in PPP publications up to *t* (excluding the focal academic i's publications) as proportion of all keywords used on PPP publications and dividing this by the number of times the keyword appeared on publications that are not part of a PPP (again excluding the focal academic i's publications).

$$w_{jt}^{i} = \frac{\sum_{PPP:n-\{i\}} \frac{n_{jt}}{\sum_k n_{kt}}}{\sum_{nPPP:n-\{i\}} n_{jt}}$$

To create the matrix of keywords we make use of txttool in Stata (Williams and Williams, 2014) and first eliminate uninformative 'stop words' (including pronouns, frequent words and numbers) from the titles, and replace some words that are synonyms, plurals and other variants with a single term. This process was aided by the Text Analyzer at Online-Utility.org (https://www.online-utility.org/text/analyzer.jsp) which was used to identify frequent words. The final matrix includes more than 8000 keywords, more than 3000 of which only appear once.

The weights *w* are larger for keywords that have appeared with a higher than average frequency on PPPs. Table B1 reports some examples of words that appear more frequently on PPPs. The first two examples refer to *fibre Bragg gratings*, a technology that appears disproportionally on PPPs compared to publications that are not linked to a patent. The keywords with the highest weights are *stellate cells* and *clathrate hydrates*, referring to research in biochemistry and chemical engineering respectively. Low weights are assigned to words that appear frequently on non-PPPs but are uncommon on PPPs. These include atom and semiconductor, as well as various chemical elements, such as aluminium.

After assigning each keyword the appropriate weight and taking the sum over all keywords on academic *i*'s publications, we get to the composite patentability measure, which, in our case, takes values between 0 and 6. This measure "increases in the degree to which keywords in the titles of a focal academic's publications have appeared relatively more frequently in the titles of [PPPs by] other academics" (Azoulay et al. 2009: 672). This score thus represents the patentability of the academic's research. After multiplying by 100, the score that is included as outcome variable in the model ranges from 0 to 600 with a mean of 9 among all academics and a mean of 16.7 amongst those with a score larger than zero.

Appendix C: Alternative outcome measures

As a robustness check we estimate our models for four alternative outcome measures as described in section 4.2: *PROCEEDINGS, AV.IMPACT, INDPUB* and *PATENT*. The descriptive statistics for the four measures are reported in Tables 1 and 2 and correlations in Appendix Table A2. They show that the mean number of proceedings per academic per year is 1.06, and thus lower than the number of publications. The average impact factor is 0.75 and highly correlated with citation numbers (ρ = 0.5883). Both, *PROCEEDINGS* and *AV.IMPACT* factor are highest for academics that receive industry and public grants. The mean share of industry co-authored publications is 9%, and 14% for years with at least one publication. The share is higher for academics with some industry funding at 14-15% of publications. The mean share of academic-year observations with at least one patent is 6% and significantly higher for academics with both types of funding.

The results of the parametric estimations (Figure C1a and C1b) show that *PROCEEDINGS* increase with funding but that there is a negative joint effect of public and industry funding, thus confirming the results of the publication equation. *AV.IMPACT* increases only with public but not industry funding, in line with results for citations and basic publications. The joint effect is negative suggesting that those who receive funding from public and private sponsors publish in lower impact journals than those that receive funding only from public sources. In this regard *AV.IMPACT* differs from citation counts where the interaction effect was positive for higher values of industry funding. The estimated dose response function for the robustness variables *PROCEEDINGS* and *AV.IMPACT* are similar to those for publication numbers and citation counts discussed in the main text. Figure C2a illustrates these effects graphically. Figure C2b depicts the estimated marginal impact of public funding at different percentiles of industry funding and confirms declining marginal effects of public funding for higher levels of industry funding for *PROCEEDINGS,* but not for *AV.IMPACT.*

Using *INDPUB* and *PATENT* we find, unlike for patentability, a positive and independent (insignificant joint) effect of both types of funding for most of the industry funding distribution. In the dose response function estimation, *PATENT* probability increases with both funding types, but especially with industry funding, while *INDPUB* does not increase with higher funding levels of any type. The joint effect is insignificant. Thus, the complementarity found for *PATENTABILITY* is not confirmed, but neither do we find strong evidence for a substitution effect suggesting additivity of different types of funding in the production of commercially oriented research. While *PATENTABILITY* measures commercially oriented research in general, industry co-authorship and patenting require collaboration on research outcomes and/or efforts going beyond research. Not all academics that produce commercially oriented, patentable research may have such skills, which may explain the differences observed here.

[Figures C1, C2a and C2b about here]

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Figures

Figure 1a: Predicted Margins and Marginal Effects of Funding on Publication numbers

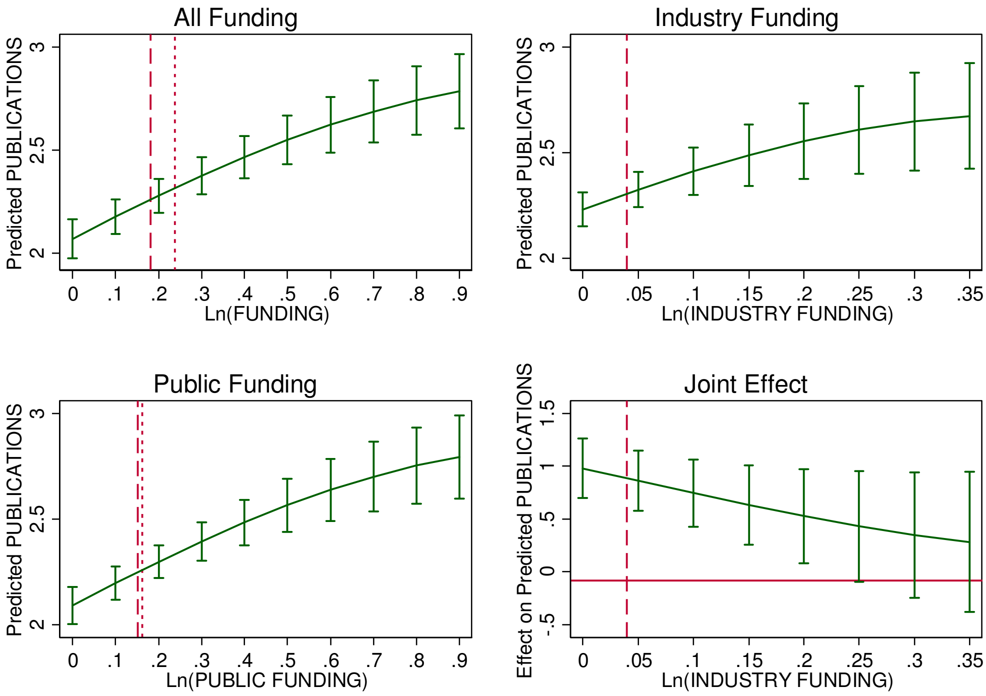


Figure 1b: Predicted Margins and Marginal Effects of Funding on Mean Citations

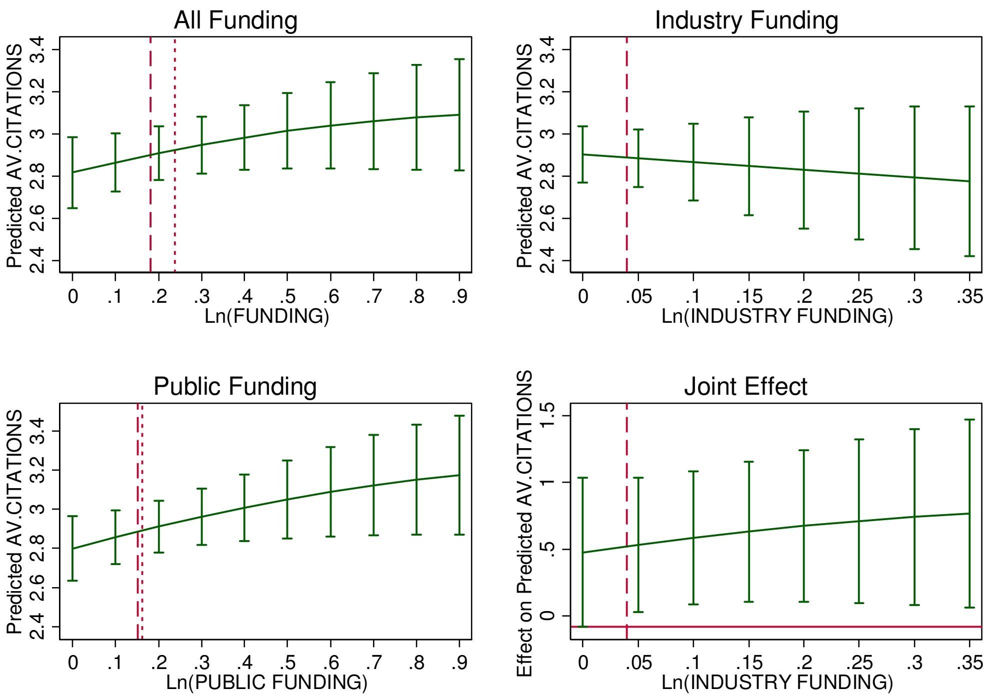


Figure 1c: Predicted Margins and Marginal Effects of Funding on Basic Publications

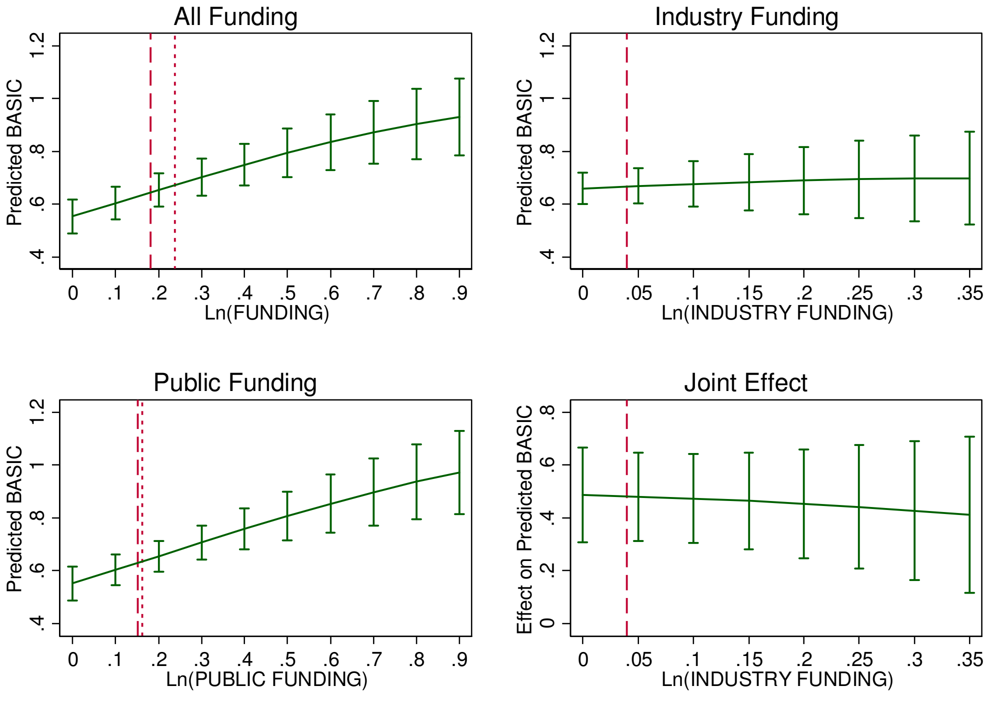
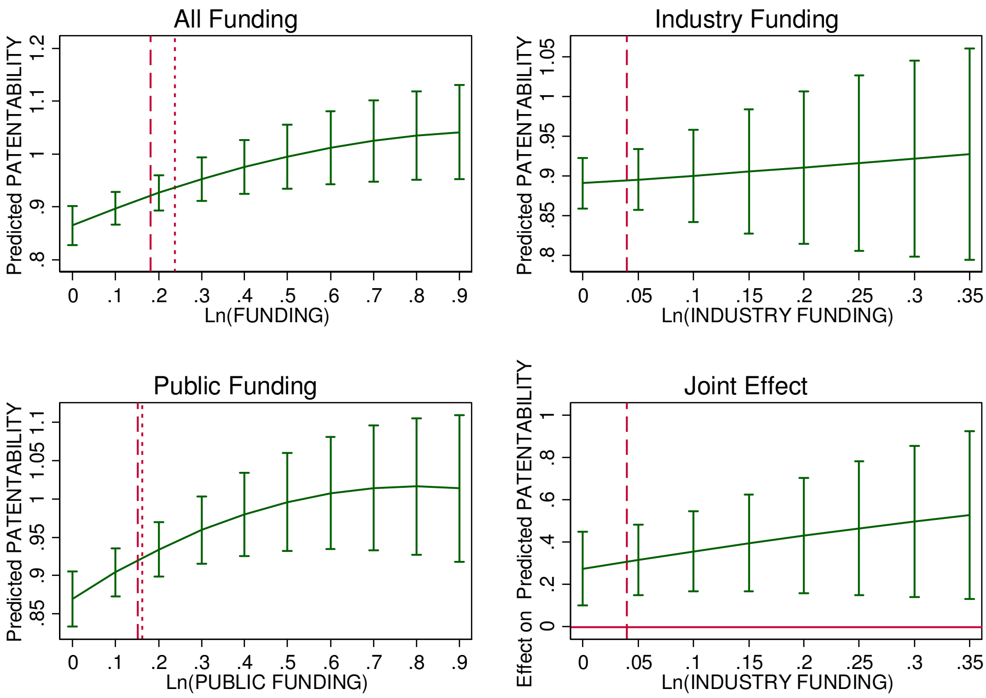
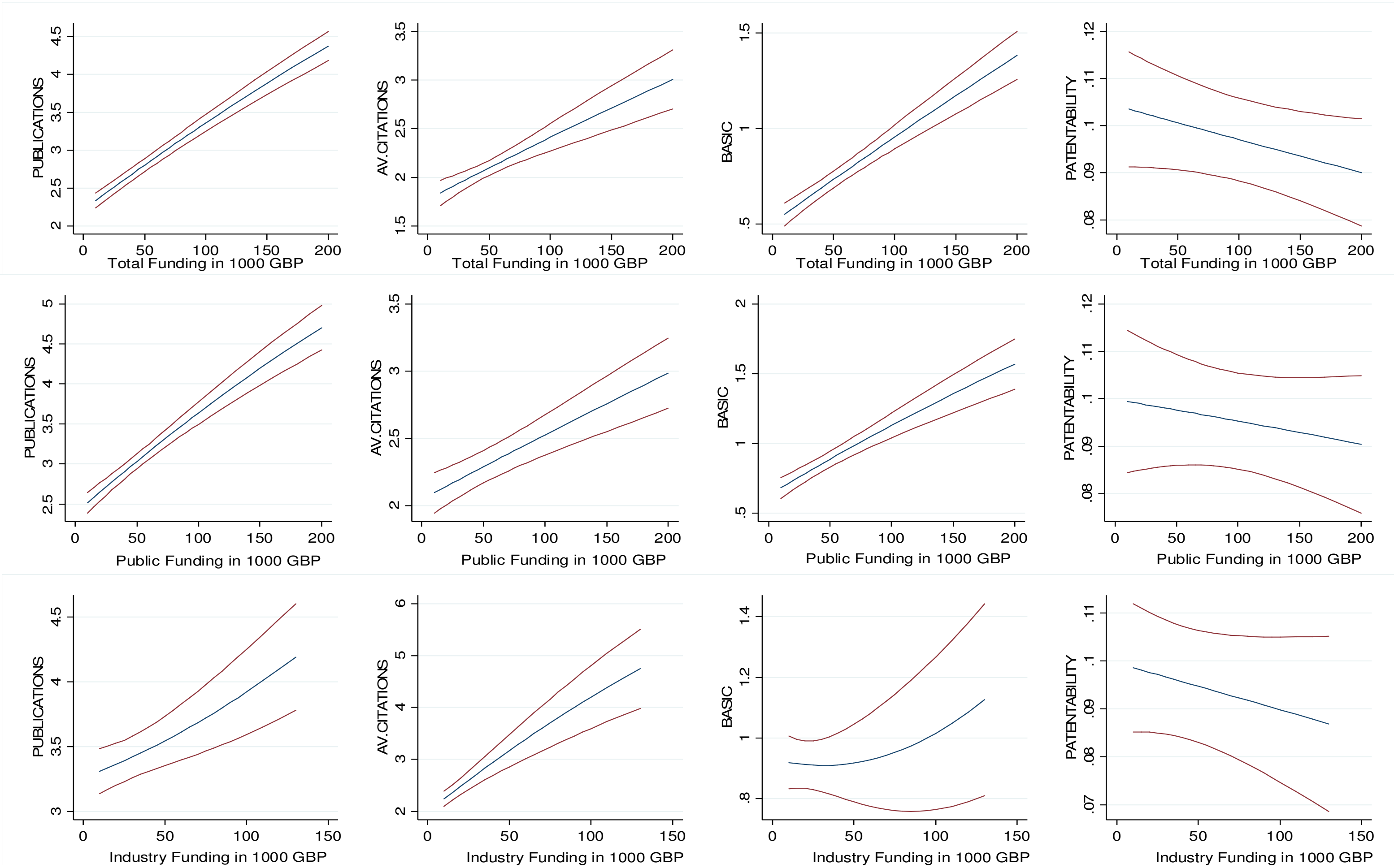


Figure 1d: Predicted Margins and Marginal Effects of Funding on Patentability



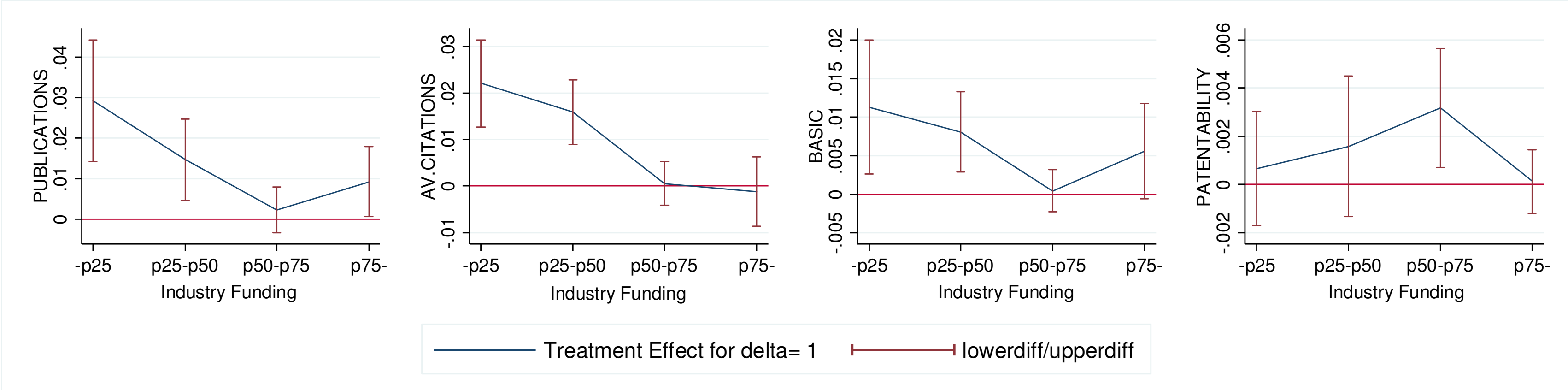
Note [Figures 1a-1d]: Vertical dashed line indicates the sample mean; vertical dotted line the 75th percentile. The 75th percentile for industry funding is zero. 90% confidence intervals are reported. Slopes for the joint effect are significant where confidence intervals do not cross the horizontal red line.

Figure 2a: Dose Response Functions by funding type on Publication numbers, av. citations, basic publications and patentability



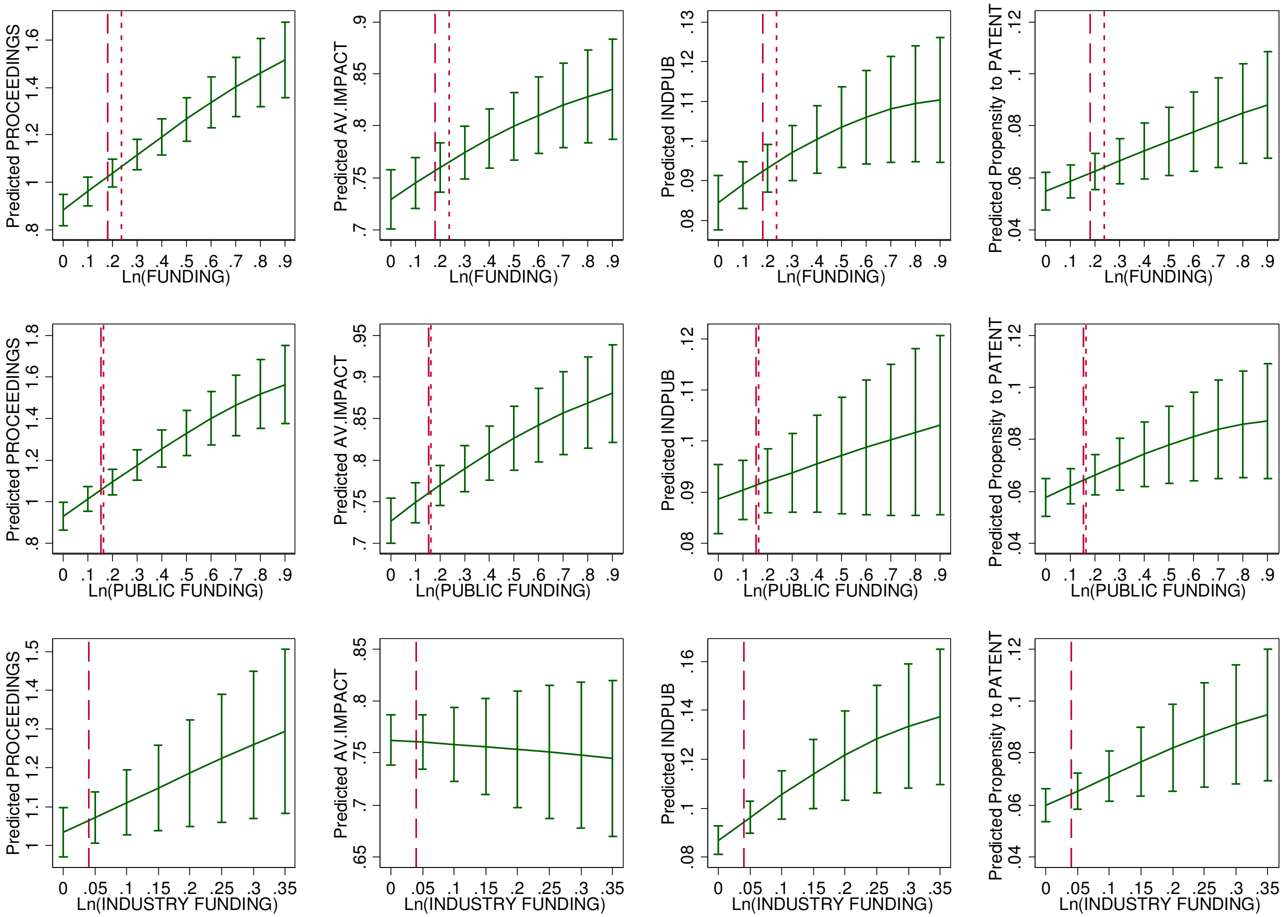
Note: Dose response functions with 95% confidence bands are reported.

Figure 2b: Change in the Dose Response Function at the mean of public funding at selected values of the industry funding distribution



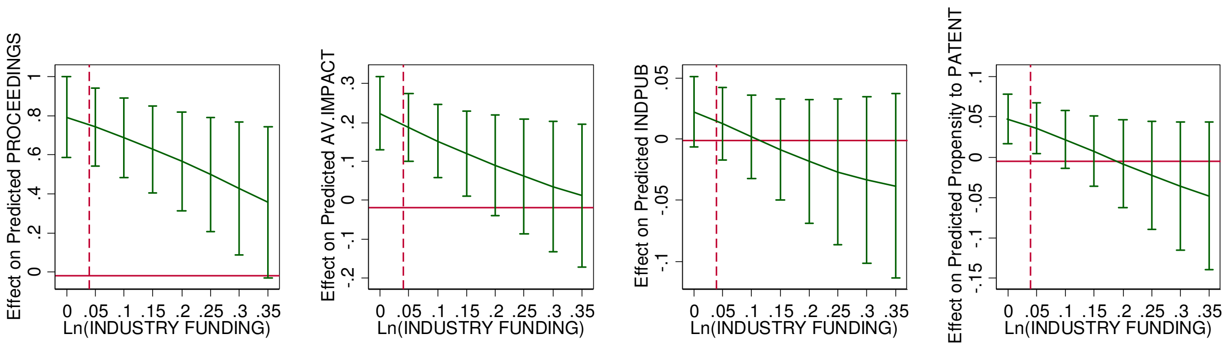
Note: 90% confidence intervals are reported. Slopes for the joint effect are significant where confidence intervals do not cross the horizontal red line.

Figure C1a: Marginal Effects of Funding on Proceedings, Average Journal Impact, Share of Industry Publications and Patenting Propensity



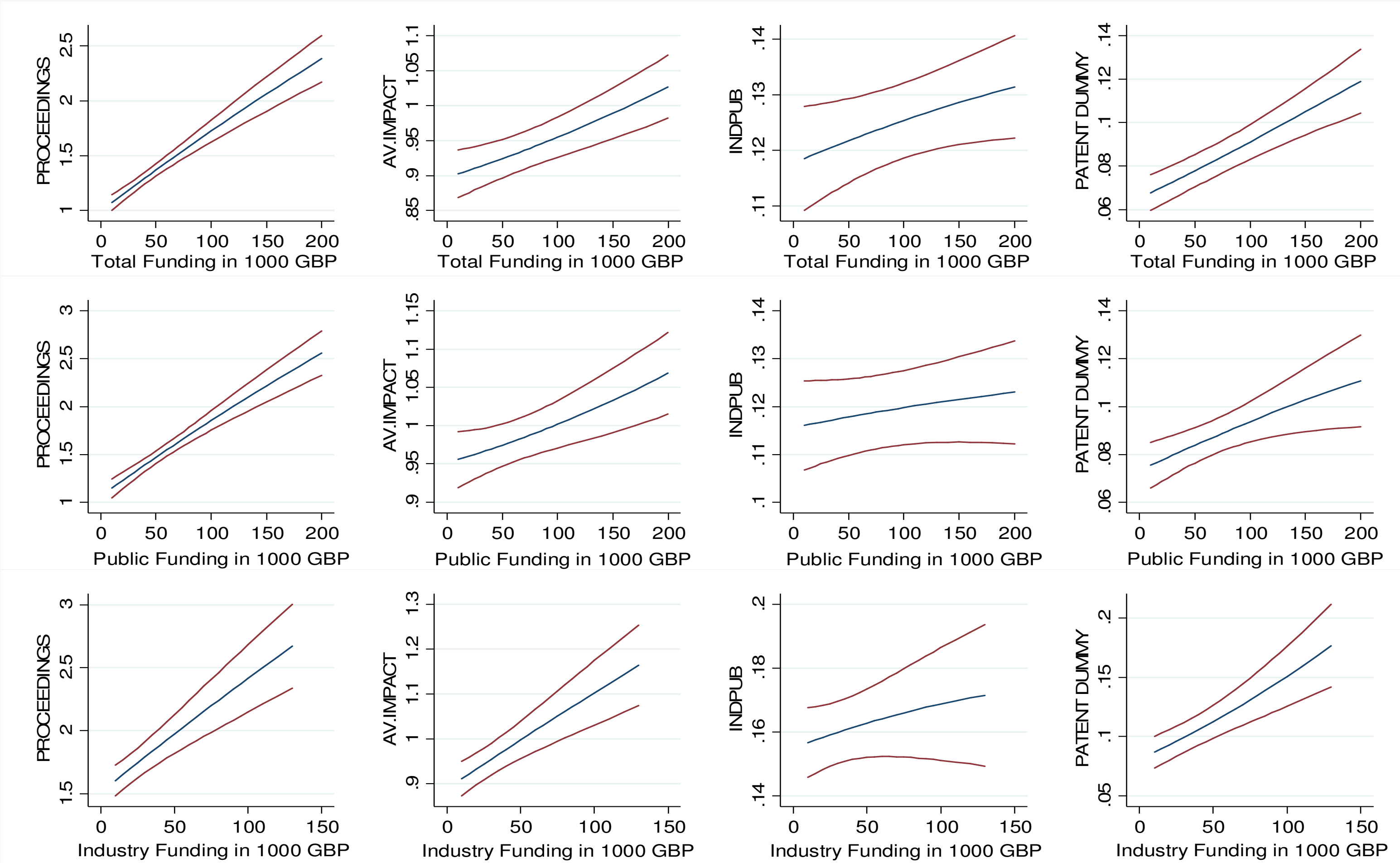
Note: Vertical dashed lines indicate the sample mean; vertical dotted lines the 75th percentile. The 75th percentile for industry funding is zero. 90% confidence intervals are reported. Effect on PROCEEDINGS and AV.IMPACT are estimated using Poisson estimations, INDPUB using fractional logits and PATENT propensity using logit models.

Figure C1b: Joint effect of public and industry funding on Proceedings, Average Journal Impact, Share of Industry Publications and Patenting Propensity



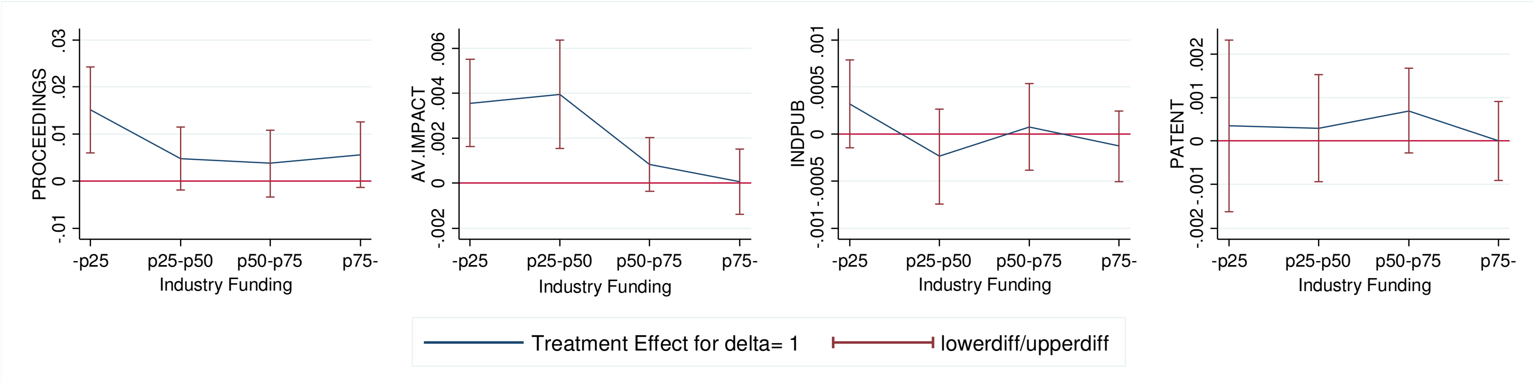
Note: Vertical dashed lines indicate the sample mean; 90% confidence intervals are reported. Slopes for the joint effect are significant where confidence intervals do not cross the horizontal red line. Effect on PROCEEDINGS and AV.IMPACT are estimated using Poisson estimations, INDPUB using fractional logits and PATENT propensity using logit models.

Figure C2a: Dose Response Functions by funding type for Proceedings, Average Journal Impact, Share of Industry Publications and Patenting Propensity



Note: Dose response functions with 95% confidence bands are reported.

Figure C2b: Change in the Dose Response Function at the mean of public funding at selected values of the industry funding distribution for alternative outcome measures



Note: 90% confidence intervals are reported. Slopes for the joint effect are significant where confidence intervals do not cross the horizontal red line.

Tables

Table 1: Descriptive statistics (4,789 observations)

	Mean	SD	Min	Max
Output measures				
$PUBLICATIONS_{it}$ (Publication number)	2.26	3.20	0	32
$AV.CITATIONS_{it}$ (Mean 5 yr citation number)	2.88	5.41	0	143
$BASIC_{it}$ (Publication number in Basic journals)	0.64	1.86	0	24
$PATENTABILITY_{it}$ (Patentability of published research)	8.95	32.07	0	600
Funding measures(in 100,000 GBP)				
$FUNDING_{it-1}$	0.32	0.95	0	12.12
$PUBLIC\_FUNDING_{it-1}$	0.26	0.84	0	11.67
$INDUSTRY\_FUNDING_{it-1}$	0.06	0.27	0	7.22
Individual characteristics				
$PROFESSOR_{it-1}$	0.34	0.47	0	1
$FEMALE_{i}$	0.07	0.25	0	1
NO_PHD_{i}	0.07	0.25	0	1
PHD_AGE_{i}	18.61	10.47	0	49
BIO_{i}	0.07	0.26	0	1
$PHYSICS_{i}$	0.15	0.36	0	1
$MECHANICAL_{i}$	0.13	0.34	0	1
$ELECTRICAL_{i}$	0.22	0.41	0	1
$CHEMICAL_{i}$	0.15	0.36	0	1
$CIVIL_{i}$	0.21	0.41	0	1
University characteristics				
SSR_{it} (Student-Staff-Ratio)	14.13	4.17	6.90	26.40
TSR_{it} (Total Staff-Support Staff-Ratio)	2.06	0.61	1.05	4.92
RSR_{it} (Researchers-Academic Staff-Ratio)	0.64	0.38	0	1.91
CONTRACTS $SHARE_{it}$ (over total income)	19.95	5.90	4.85	29.43
Robustness output measures				
$PROCEEDINGS_{it}$ (Proceedings number)	1.06	2.41	0	41
AV.IMPACT (Mean journal impact factor)	0.75	0.96	0	11.66
$INDPUB_{it}$ (Share of industry-co-authored publications)	0.09	0.23	0	1
$PATENT_{it}$ (Patent dummy)	0.06	0.24	0	1

Table 2: Means by funding structure

	1	2	3	4	5
Funding	Public=0; Industry=0	Public=0; Industry>0	Public>0; Industry=0	Public>0; Industry>0	Anova F-Test
# observations	2845	303	1104	537	Sig.
# academics	650	140	364	194	
Output measures					
$PUBLICATIONS_{it}$	1.75	1.98	2.73***	4.12***	***
$AV.CITATIONS_{it}$	2.48	2.46	3.37***	4.25***	***
$BASIC_{it}$	0.49	0.25**	0.79***	1.40***	***
$PATENTABILITY_{it}$	8.85	8.56	10.02	7.45	
Funding measures (in 100,000 GBP)					
$FUNDING_{it-1}$	0.00	0.22***	0.62***	1.42***	***
$PUBLIC\_FUNDING_{it-1}$	0.00	0.00	0.62***	1.05***	***
$INDUSTRY\_FUNDING_{it-1}$	0.00	0.22***	0.00	0.38***	***
Alternative output measures					
$PROCEEDINGS_{it}$	0.72	1.10***	1.42***	2.09***	***
$AV.IMPACT_{it}$	0.64	0.66	0.93***	1.06***	***
$INDPUB_{it}$	0.07	0.14***	0.10***	0.15***	***
$PATENT_{it}$	0.04	0.06	0.07***	0.13***	***

Note: ***,**,* indicate a significance level of 1%, 5% 10%. Stars in columns 2-4 indicate significance of mean comparison with column 1 (observations with no funding). Analysis of variance (column 5) compares the four groups of academics.

Table 3: Overall funding equations

	1		2		3		4	
VARIABLES	***PUBLICATIONS$_{it}$***		***AV.CITATIONS$_{it}$***		***BASIC$_{it}$***		***ln[PATENTABILITY]$_{it}$***	
	POISSON		POISSON		POISSON		OLS	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
ln[FUNDING]$_{it-1}$	0.526***	0.098	0.174	0.129	0.903***	0.210	0.341***	0.114
ln[FUNDING^2]$_{it-1}$	-0.218***	0.060	-0.079	0.062	-0.362***	0.104	-0.161***	0.058
PROFESSOR$_{it-1}$	0.334***	0.058	0.318***	0.062	0.007	0.145	0.210***	0.047
FEMALE$_i$	0.050	0.080	-0.109	0.099	0.293	0.191	-0.047	0.078
NO_PHD$_i$	-0.743***	0.149	-0.639***	0.201	0.519	0.418	-0.530***	0.087
PHD_AGE$_{it}$	-0.016***	0.003	-0.014***	0.004	-0.009	0.007	-0.008***	0.002
BIO$_i$	0.188**	0.090	0.536***	0.099	1.685***	0.221	0.117	0.085
PHYSICS$_i$	0.287***	0.077	0.306***	0.100	1.777***	0.229	0.047	0.066
MECHANICAL$_i$	0.035	0.082	-0.037	0.105	0.552**	0.233	-0.017	0.068
ELECTRICAL$_i$	0.172**	0.072	0.225**	0.097	1.100***	0.225	0.102	0.062
CHEMICAL$_i$	0.378***	0.075	0.417***	0.096	1.570***	0.216	0.095	0.063
CIVIL$_i$ (Reference)								
SSR$_{it}$	-0.021***	0.008	-0.009	0.009	-0.045***	0.016	-0.002	0.006
TSR$_{it}$	0.101**	0.051	0.042	0.099	-0.225	0.155	0.081	0.057
RSR$_{it}$	0.069	0.075	-0.039	0.092	0.202	0.166	0.138*	0.072
ln[Pub_Mean|Cit_Mean]	0.366***	0.046	0.200***	0.038	0.671***	0.093		
[Pub_Mean|Cit_Mean=0]	-0.684***	0.098	-0.450***	0.089	-0.829***	0.227		
L.Dependent Variable Stock	0.015***	0.003	0.011***	0.002	0.023***	0.005	0.001*	0.000
Joint sign. of university dummies $\chi2$ (14)	79.75***		94.95***		66.33***		4.93***	
Joint sign. of subject dummies $\chi2$ (5)	35.35***		48.69***		89.01***		1.21	
Joint sign. of year dummies $\chi2$ (5)	21.01***		7.38		13.54**		4.31***	
Log-likelihood	-8629.400		-14978.507		-4041.975		-7885.202	
F							10.14***	
# academics	807		807		807		807	
# observations	4789		4789		4789		4789	

Note: ***,**,* indicate a significance level of 1%, 5% 10%. Robust clustered standard errors in parentheses; clustered by individual academic. Models include a constant.

Table 4: Split funding equations

VARIABLES	1 ***PUBLICATIONS***$_{it}$ POISSON Coef.	 SE	2 ***AV.CITATIONS***$_{it}$ POISSON Coef.	 SE	3 ***BASIC***$_{it}$ POISSON Coef.	 SE	4 ***Ln[PATENTABILITY]***$_{it}$ OLS Coef.	 SE
ln[PUBLIC_FUNDING]$_{it-1}$	0.575***	0.108	0.197	0.147	0.974***	0.247	0.342***	0.122
ln[PUBLIC_FUNDING^2]$_{it-1}$	-0.251***	0.067	-0.074	0.077	-0.354***	0.122	-0.227***	0.064
ln[INDUSTRY_FUNDING]$_{it-1}$	1.177***	0.373	-0.201	0.535	0.483	0.861	-0.039	0.479
ln[INDUSTRY_FUNDING^2]$_{it-1}$	-1.387***	0.509	0.052	0.785	-0.481	0.987	0.115	0.669
ln[PUBLIC_FUNDING]$_{it-1}$# ln[INDUSTRY_FUNDING]$_{it-1}$	-1.969**	0.883	0.535	1.031	-0.362	1.775	0.872	1.199
ln[PUBLIC_FUNDING^2]$_{it-1}$# ln[INDUSTRY_FUNDING]$_{it-1}$	0.897*	0.503	-0.214	0.489	-0.175	0.839	-0.021	0.648
ln[PUBLIC_FUNDING]$_{it-1}$# ln[INDUSTRY_FUNDING^2]$_{it-1}$	1.918*	1.026	-0.397	1.318	-0.466	1.814	-0.352	1.284
ln[PUBLIC_FUNDING^2]$_{it-1}$# ln[INDUSTRY_FUNDING^2]$_{it-1}$	-0.759	0.580	0.161	0.595	0.653	0.899	-0.166	0.691
PROFESSOR$_{it-1}$	0.329***	0.057	0.318***	0.062	-0.002	0.140	0.208***	0.046
FEMALE$_i$	0.063	0.081	-0.105	0.102	0.327*	0.193	-0.058	0.078
NO_PHD$_i$	-0.725***	0.146	-0.634***	0.202	0.527	0.414	-0.533***	0.088
PHD_AGE$_{it}$	-0.015***	0.003	-0.014***	0.004	-0.008	0.007	-0.008***	0.002
BIO$_i$	0.189**	0.087	0.537***	0.099	1.673***	0.220	0.119	0.085
PHYSICS$_i$	0.298***	0.075	0.311***	0.100	1.773***	0.229	0.053	0.066
MECHANICAL$_i$	0.037	0.080	-0.032	0.105	0.557**	0.234	-0.015	0.068
ELECTRICAL$_i$	0.179**	0.070	0.231**	0.097	1.119***	0.225	0.101	0.062
CHEMICAL$_i$	0.379***	0.073	0.414***	0.095	1.563***	0.216	0.100	0.063
CIVIL$_i$ (Reference)								
SSR$_{it}$	-0.021***	0.008	-0.009	0.009	-0.044***	0.016	-0.002	0.006
TSR$_{it}$	0.095*	0.051	0.039	0.099	-0.259*	0.153	0.082	0.057
RSR$_{it}$	0.050	0.072	-0.043	0.093	0.143	0.157	0.137*	0.073
ln[Pub_Mean|Cit_Mean]	0.360***	0.047	0.198***	0.038	0.666***	0.093		
[Pub_Mean|Cit_Mean=0]	-0.680***	0.098	-0.450***	0.089	-0.833***	0.227		
L.Dependent Variable Stock	0.015***	0.003	0.011***	0.002	0.023***	0.006	0.001*	0.000
Joint sign. of university dummies χ2 (14)	82.61***		97.39***		64.70 ***		4.87***	
Joint sign. of subject dummies χ2 (5)	36.64***		48.25***		87.63***		1.20	
Joint sign. of year dummies χ2 (5)	19.02***		7.45		11.59**		4.35***	
Log-likelihood	-8612.704		-14969.750		-4022.917		-7882.386	
F							9.70***	
# academics	807		807		807		807	
# observations	4789		4789		4789		4789	

Note: ***,**,* indicate a significance level of 1%, 5% 10%. Robust clustered standard errors in parentheses; clustered by individual academic. Models include a constant.

Annex A

Table A1: List of Universities

University Name	**Academics**	**Region**
Brunel University	48	London
City University London	23	London
Queen Mary University	31	London
University of Reading	22	South East
University of Cambridge	122	East
University of Essex	26	East
University of Leicester	29	East Midlands
Loughborough University	123	East Midlands
University of Durham	21	North East
Lancaster University	10	North West
University of Sheffield	100	Yorkshire
University of Edinburgh	53	Scotland
University of Glasgow	63	Scotland
University of Strathclyde	97	Scotland
University of Swansea	46	Wales
Total	**807***	

*Academics can change university within the sample. Therefore, numbers do not add up to 807.

Table A2: Correlation matrix for individual level variables (4,789 observations)

		1	2	3	4	5	6	7	8	9	10	11
1	$PUBLICATIONS_{it}$	1.000										
2	$AV.CITATIONS_{it}$	0.322***	1.000									
3	$BASIC_{it}$	0.729***	0.270***	1.000								
4	$\ln(PATENTABILITY_{it})$	0.245***	0.234***	0.109***	1.000							
5	$PROCEEDINGS_{it}$	0.312***	0.130***	0.170***	0.058***	1.000						
6	$AV.IMPACT_{it}$	0.465***	0.588***	0.467***	0.332***	0.134***	1.000					
7	$INDPUB_{it}$	0.135***	0.122***	0.054***	0.119***	0.094***	0.157***	1.000				
8	$PATENT_{it}$	0.139***	0.077***	0.135***	0.016	0.148***	0.122***	0.109***	1.000			
9	$\ln(FUNDING_{it-1})$	0.271***	0.111***	0.184***	0.075***	0.263***	0.166***	0.074***	0.104***	1.000		
10	$\ln(PUBLIC\_FUNDING_{it-1})$	0.253***	0.103***	0.174***	0.067***	0.245***	0.161***	0.052***	0.082***	0.959***	1.000	
11	$\ln(INDUSTRY\_FUNDING_{it-1})$	0.176***	0.077***	0.133***	0.057***	0.169***	0.086***	0.080***	0.115***	0.552***	0.313***	1.000

Note: ***,**,* indicate a significance level of 1%, 5% 10%.

Table A3: Maximum Likelihood Estimation of the generalized propensity score (Generalized Linear Models)

Treatment variable:	ALL FUNDING		PUBLIC FUNDING		INDUSTRY FUNDING	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
PROFESSOR	0.964	0.080 ***	0.909	0.089 ***	0.523	0.105 ***
FEMALE	-0.105	0.132	-0.157	0.161	0.296	0.176 *
ln(PHD_AGE)	-0.338	0.067 ***	-0.369	0.075 ***	-0.146	0.100
BIO	0.134	0.138	0.081	0.155	0.260	0.194
PHYSICS	0.328	0.095 ***	0.289	0.101 ***	0.704	0.163 ***
MECHANICAL	0.302	0.101 ***	0.180	0.111	0.863	0.157 ***
ELECTRICAL	0.183	0.097 *	0.174	0.103 *	0.320	0.113 ***
CHEMICAL	0.066	0.107	0.160	0.118	-0.339	0.133 **
ln[Pat_Mean]	0.012	0.119	0.123	0.146	-0.100	0.157
Pub_Mean =0	-0.109	0.107	0.091	0.124	-0.415	0.129 ***
Past FUNDING	0.372	0.113 ***				
Past PUBLIC FUNDING			0.439	0.102 ***	0.182	0.094 *
Past INDUSTRY FUNDING			0.258	0.078 ***	0.202	0.107 *
SSR	-0.016	0.008 *	-0.009	0.008	-0.036	0.016 **
NAR	0.059	0.070	0.072	0.071	-0.089	0.110
TRR	0.068	0.102	-0.019	0.109	0.553	0.164 ***
CONTR.SHARE	0.023	0.007 ***	0.019	0.008 **	0.021	0.011 *
ln[Pub_Mean]	0.181	0.041 ***	0.100	0.043 **	0.238	0.070 ***
Pub_Mean=0	0.080	0.082	0.029	0.083	0.274	0.156 *
# observations	1602		1335		700	
Log pseudolikelihood	-8558.53		-7090.85		-3059.01	

Note: Robust standard errors in parentheses. *** (**, *) indicate 1% (5%, 10%) confidence levels. These results are based on the case for *PUBLICATIONS* as outcome variable. The results from the models for the other outcome variables differ only slightly due to different pre-sample variables of the respective outcome indicator in the models. The estimation results are available upon request.

Table A4: Balancing tests of the GPS estimator

Variable	Treatment Interval 1 [1, 6] mean diff.	t-value	Treatment Interval 2 [7, 19] mean diff.	t-value	Treatment Interval 3 [20, 46] mean diff.	t-value	Treatment Interval 4 [47, 99] mean diff.	t-value	Treatment Interval 5 [100, 1846] mean diff.	t-value
PROFESSOR	-0.062	-2.832	0.013	0.787	0.030	2.256	-0.039	-1.429	-0.078	-4.834
FEMALE	0.004	0.165	-0.010	-0.517	0.008	0.502	-0.030	-2.018	0.053	2.946
ln(PHD_AGE)	-0.178	-4.226	0.023	0.645	0.046	1.611	0.022	0.755	-0.011	-0.339
BIO	-0.028	-1.168	-0.026	-1.219	-0.005	-0.287	0.008	0.536	0.011	0.607
PHYSICS	-0.020	-0.573	0.012	0.391	-0.019	-0.805	0.007	0.316	0.006	0.268
MECHANICAL	0.024	0.726	-0.009	-0.324	-0.005	-0.221	-0.008	-0.374	-0.053	-2.245
ELECTRICAL	-0.009	-0.235	0.033	0.996	0.014	0.559	0.002	0.088	-0.001	-0.024
CHEMICAL	-0.072	-2.556	0.036	1.434	-0.011	-0.546	0.011	0.541	0.007	0.292
2004	-0.002	-0.059	-0.043	-1.417	0.037	1.535	-0.007	-0.301	0.000	0.002
2005	0.051	1.459	-0.007	-0.209	-0.042	-1.710	0.004	0.170	0.023	0.842
2006	-0.045	-1.258	0.028	0.871	0.013	0.533	-0.011	-0.468	0.034	1.256
2007	-0.010	-0.283	0.005	0.156	-0.016	-0.665	0.036	1.547	-0.041	-1.561
ln[Pat_Mean]	0.010	0.390	0.000	-0.016	-0.011	-0.640	-0.013	-0.892	0.027	1.930
Pub_Mean =0	-0.054	-1.812	-0.046	-1.742	-0.015	-0.733	0.024	1.298	0.042	2.379
Past_FUNDING	0.062	2.756	0.017	0.854	-0.017	-0.988	-0.017	-0.858	-0.067	-2.827
SSR	0.519	1.663	-0.136	-0.493	-0.205	-0.934	0.265	1.196	-0.026	-0.103
NAR	0.113	2.196	-0.007	-0.144	-0.070	-1.986	0.000	-0.005	0.011	0.272
TRR	0.034	1.012	0.021	0.707	0.002	0.082	-0.027	-1.181	-0.025	-1.014
CONTR.SHARE	-0.223	-0.491	-0.496	-1.224	0.130	0.408	-0.106	-0.336	0.032	0.088
ln[Pub_Mean]	0.018	0.268	0.162	2.770	0.061	1.343	-0.079	-1.585	-0.060	-1.304
Pub_Mean=0	0.001	0.019	0.021	0.879	0.005	0.280	-0.003	-0.149	-0.003	-0.111

Note: Test that the conditional mean of the pre-treatment variables given the GPS is not different between units who belong to a particular treatment interval and units who belong to all other treatment intervals. These results are based on all *FUNDING*. Statistics for the other funding variables are available upon request.

Annex B

Table B1: Sample Title Keywords 1999 - 2006

	Number of times on PPPs $\sum_{PPP:n-\{i\}} n_{jt}$	Number of times used on non-PPPs $\sum_{nPPP:n-\{i\}} n_{jt}$	Keyword weight: $w_{jt}^{i} = \frac{\sum_{PPP:n-\{i\}} \frac{n_{jt}}{\sum_k n_{kt}}}{\sum_{nPPP:n-\{i\}} n_{jt}}$
Number of papers	685	17,843	
Number of words	4,376	103,571	
Number of unique keywords	1,395	8,567	
Bragg	31	65	0.000109
grate	62	83	0.000171
stellate	10	1	0.002285
clathrate	6	1	0.001371
atom	1	107	0.000002
aluminium	1	281	0.000001
superconductor	4	78	0.000011

Note: PPP = patent-paper-pairs, nPPP = non-patent-paper-pairs; n_j is the number of times the focal keyword appeared; n_k is the total number of keywords used on publications; i is the focal academic's publications.